February 2, 2016

Dear Editors,

In the following, we answered point-by-point to the comments raised by S. Konovalov and the second anonymous reviewer. We copied the reviewer's comments in their totality and included our answers in blue. We'd like to express our gratitude towards the reviewers for their constructive comments and to the editorial staff for their work.

Arthur Capet, on behalf of coauthors.

1 Reviewer 1: S.Konovalov

1.1 General Comments

C: *This manuscript is addressed to an extremely important issue of decline in the oxygen inventory in marine systems. This decline has been traced in many marine systems, but it is crucially important for oxygen deprived oxic/anoxic marine systems, like the Black Sea, for example. Indeed, the thickness of oxygenated waters in the Black Sea does not exceed upper 200 meters. Thus, even minor variations in the distribution of oxygen are important for this marine system. For all these reasons, the manuscript suggests valuable information and it is worth publishing in Biogeosciences.*
C: *The authors analyze data from 1955 to 2014. They split all these data in several individual periods of specific trophic- and/or climate-driven changes in the Black Sea. Except for the most recent period of 1999-2013, and specifically for the period after 2010, all results and conclusions look good and well-justified.*
C: *The major problem is in DIVA analysis of highly limited and spatially located data in 1999-2013. While DIVA analysis is explained briefly for this major tool of this work, any kind of interpolation cannot fill spatial gaps of about 80-90% of the basin area (Fig. 2, lower panel).*
A: We agree that the scarcity of the data challenges the computation of meaningful diagnostics and the production of gridded fields. Given the importance of this topic, the question is what best analysis can be made out of scarce data. Studies of the long term evolution of the Black Sea oxycline or chemocline usually make the hypothesis that these characteristics when expressed on a density scale are independent of the spatial location and of the season. Diagnostics are then obtained by averaging the information derived from punctual profiles expressed on a density scale even if they are scarcely distributed throughout the basin. Our approach to remedy to this data deficiency and to strengthen the meaning of our diagnostics is (1) to exploit at best the information that can be gathered from an extended dataset and (2) to complement the analysis with independent estimates from Argo, acknowledging the issue of their comparability. Regarding (1), our working hypothesis is that recurrent spatial structure, that can be evidenced from data-rich period, could and should be exploited to enhance the analysis of data from the data-poor period. To be clear : Spatial analyses are made gathering data for the whole period. Temporal trends are then identified as the average misfit between data of a given year and the climatological spatial analyses. We understand that our succinct description of the DIVA analysis tool led to confusion. For better clarity we now included an appendix to describe the method, in addition to the previous reference to Capet et al. (2014) where the method is detailed and applied on synthetic and real (Black Sea CIL) case studies.

C: *This problem seems even more serious, when DIVA analysis is applied to the position of 20 μM of oxygen, while the authors suggest that it varies versus depth and density.*
A: The position of 20 μM of oxygen is expressed in terms of depth and density and derived for every profile. Reducing the dimensionality of the problem by extracting scalar diagnostics from vertical profiles simplifies both the analysis (2D interpolation of specific diagnostics instead of diagnostic derivation from 3D interpolation) and the presentation/discussion of the results. We considered three different diagnostics to show that the overall conclusion (deoxygenation of Black Sea) does not strictly depend on the choice of a specific diagnostic. In particular the temporal artifacts induced by horizontal variability of these diagnostics is addressed by consid-

ering both depth and density coordinates for the oxygen penetration depth, and through the DIVA detrending procedure.

C: *It is absolutely important to show that DIVA analyses is correct when it is applied to highly limited and spatially irregular distribution of data in 1999-2013.*
A:

1. In fact, the situation is worse than previously thought, as we noticed that some Argo data were reported in the WOD database and erroneously mistaken for ship-based data. We now carefully checked the WOD set to dissociate ship-based data (analyzed using DIVA) from Argo data (see revised Figs. 1, 2 below).
2. The DIVA detrending analysis is applied on the ship-based data set as a whole, not period by period. This procedure aims at identifying both spatial variability and temporal trends from the whole dataset. Spatial climatology are constructed for the entire period and from the whole data set. For the spatial analyses, the detrending consists in considering the anomaly associated to each data due to its location in time (ie. the trend associated with the year containing the data). Temporal trends are assessed for each particular year. For these temporal analyses, the detrending consists in considering the anomalies associated with the spatial location of each data. The procedure is iterative ie. guess for spatial and temporal trends are re-estimated together and updated until reaching convergence.
3. We hope the equations provided in the extended description of the algorithm would make it clearer (the additional Appendix is given below).
4. The influence of data from the latest period on the spatial climatology is of minor importance given the low amount of data compared to data from previous periods.
5. The main and remaining question therefore regards the temporal trend given for 2001, 2003, 2005. The basic estimates for these trends would be the average of the diagnostic obtained from the profiles of those year. The DIVA estimates are based on those average values but apply a correction considering the spatial and seasonal distribution of the data. This correction stems from the spatial variability, which are identified from the whole dataset and are therefore not tainted from the scarcity of data for these years. In other words, the basis estimates are weakened by the lack of data, but the DIVA corrections are not.

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C: *Another problem is that the major part of observational oxygen data are from Winkler titration of water from Niskin samplers, while data for 2012-2013 are from Argo floats. I do support Argo floats, but the authors have to demonstrate that these two types of oxygen data are precisely comparable.*
A:

1. Argo data erroneously introduced in the "ship-based" dataset have been removed (see Figs. 1, 2).
2. The calibration and error of Argo oxygen profiles data for the two Argo floats presented in the former version of the manuscript are discussed in Stanev et al. (2013) (see paragraphs 8 and 10, hereafter). *"[8] The sensor for temperature and salinity was CTD SBE 41, and the one for oxygen was Anderaa Oxygen Optode 3830. Oxygen sensors show little or no drift and high accuracy [Johnson et al., 2009; Riser and Johnson, 2008]. In the Black Sea, there is a "natural calibration" every time when the float produces a new profile because there is a "solid zero" at depth. Analysis of data in the anoxic layers never showed values higher than 1 μM, which can roughly be taken as an error estimate for the analyses presented in this paper. Furthermore, comparisons with historical observations (see next section) demonstrated that the sensors used provide credible results" "[10] The comparison between profiling float data and historical observations demonstrates the consistence of the new measurements. Furthermore, it enables to objectively decipher oxic conditions and changes in the Black Sea hydro-chemistry in the area of suboxic zone. In the following, the advantages of the two data sets (long-term sampling in the historical data and continuous sampling in the profiling float data) are put together in a complementary manner."*
3. Additional Argo profiles are considered in the revised manuscript. Those were collected, checked and made freely available by the International Argo Program, part of the Global Ocean Observing System, and the national programs that contribute to it (http://www.argo.ucsd.edu, http://argo.jcommops.org). Only good quality-checked data were considered
(see Argo user-manual, http://archimer.ifremer.fr/doc/00187/29825/40575.pdf).

4. Several studies adress the error of Argo real-time oxygen data (e.g., Bittig and Körtzinger, 2015; Takeshita et al., 2013; Johnson et al., 2015). Demonstrating that the Black Sea real-time Argo data are precisely (ie, at fine scales) comparable with historical Winkler data, or identifying the relevant correction, is beyond the scope of the present study which addresses monthly to decadal time scales. Evenly distributed small scales error (eg., difference between ascending and descending profiles due to sensor time response) were thus filtered by the temporal smoothing. However, a systematic error is not strictly excluded which could reach an underestimation of 10 μM (Virginie Thierry, IFREMER, personnal communication, January 2016). Therefore, we evaluated a "worst-case" scenario in the analysis of Argo data by considering a systematic underestimation of oxygen concentration by 10μM (Fig. 5).

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C: *I know, for example, that Winkler titration data for 2013 reveal sigma–t = 15.60–15.65 for 20 μM of oxygen and a rather isopycnal spatial distribution (look for the attached figure), while the authors suggest about 15.40 and a spatially variable distribution.*
A:

1. A confusion occurred in the former manuscript regarding the computation of the potential density scale for the different data sources. In the revised manuscript, the density scale used is the potential density anomaly, σ_θ , computed from the different data sources following TEOS-10 standards and scripts (http://www.teos-10.org/).
2. The value derived from the Argo are now presented separately on additional Fig. 4. Ignorant of the spatial distribution of the data presented by the reviewer we are unable to comment on the spatial variability.
3. As commented previously, we acknowledge an inherent uncertainty on the Argo real-time data. As we lack Winkler data whithin the Argo years, our approach is to consider a possible large error on the Argo data (10μM) when discussing the results.

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C: *I recommend an in-depth analysis of that patchiness in Fig. 3c and data for 2012–2013.*
A: We thank the reviewer for pointing us two mistakes in our previous submission (already adressed above): (1) Data reported in the WOD database for 2012-2013 (also 2010) were indeed Argo data and were therefore removed from the DIVA analysis. (2) Miscomputation of density anomaly from different data sets resulted in the patchiness of figure 3c. This figure has been updated and reveals interesting features, to be discussed in more details. In short, the spatial analysis of oxygen penetration density levels suggests diapycnal ventilation in the periphery of the basin where the bathymetry is steep.

1.2 Specific Comments

C: *Title. The discussed decline is not that "recent". I would suggest to drop "recent" and to limit to "Decline of the Black Sea oxygen inventory".*
A: The title has been changed accordingly.

C: *Page 16235, line 5. Consider "the surface layer of a lower salinity".*
A: The sentence has been changed to *"... that separates the surface layer (of low salinity due to river inflow) from the deeper layer (of high salinity due to inflowing Mediterranean seawater), restraining ventilation to the upper layer".*

C: *Page 16235, line 9. Murray et al. (1989) considered* 10 μM *of oxygen and the first appearance of sulfide because they analyzed high quality oxygen data from the KNORR cruise.* 20 μM *of oxygen were applied later to analyze historical oxygen data of lower quality*
A: We mainly reffered to Murray et al. (1989) for introducing the suboxic layer. The choice of 20 μM as a thresold for analysis is presented later in the result section 2.2. We added the precision suggested by the reviewer in the manuscript

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C: *Page 16239. A better description of DIVA analysis is needed.*
A: We added a description of the DIVA software and DIVA detrending algorithm in a dedicated appendix, although a full description and skill assessment on synthetic and real cases can be found in Capet et al. (2014).

C: *Page 16239. What are the trends in original data?*
A: If this concerns the sentence *"A new data set is constructed by subtracting the trends from the original data."*, it is a misunderstanding. The sentence should read "A new data set is reconstructed out of the original dataset by subtracting the trends" or "New Set = Original Set - Trends". This is clarified in the appendix.

C: *Page 16239. What is "detrended" spatial climatology?*
A: A spatial climatology constructed out of the entire dataset but removing from each data the anomaly associated with its location in time, using the temporal trends identified in the iterative process. As the same remarks was raised by to reviewer #2, we avoided this confusing expression in the revised manuscript.

C: *Page 16239. If a spatial climatology is applied to every specific year, it is hardly correct for both depth and density data.*
A: The three spatial climatologies (one per diagnostic) are computed from the entire dataset (see above comments). Ignoring the spatial variability also constitutes a strong assumption, if only a simpler one. Here we consider that a statistically recurrent spatial structure of the diagnostics can (and should) be exploited to enhance the interpretation of the temporal variability depicted by the data. In the case where there would be no such recurrent spatial structure, either because spatial variations are low, either because spatial variations canceled when they are averaged in time (ie. they are not "recurrent"), the spatial climatology would be flat (ie., small compared to temporal variations) and bear low impact on the analyzed temporal trends (which would then be close to the average value for given years).

C: *Page 16240, line 2. Are these spatial variations? What are trends?*
A: We changed the titles of section 3.1 and 3.2 to "Spatial variability" and "Temporal variability".

C: *Page 16240, line 17. I would discuss a decline in oxygen penetration depth for a period, rather than an average rate because it definitely varies in time (Fig. 4).*
A: The linear trends were not given because we consider the decrease to be linear, but to provide a long-term "averaged" decreasing rate. However the discussion can be extended considering the different periods.

C: *Page 16244, line 14. It does not illustrate any decoupling because it is not discussed and/or analyzed in this work.*
A: We removed the last paragraph.

2 Reviewer 2: Anonymous

2.1 General Comments

C: *This paper aims to reassess estimates of trends oxygen content in the Baltic taking into accounts the past 60 years, split into periods of different physical and biological dynamics.*
A: It is not clear to which extent the repeated mistake "Baltic Sea" instead of "Black Sea" affects the reviewing comments. We considered that it was just a word mistake and addressed most of the comments reading "Black Sea" instead of "Baltic Sea".

C: *The authors interpolate data using an interpolation scheme which attempts to account for variable data density in the hopes of being able to compare more data sparse periods to the rest of the dataset. Overall, I agree fully with and would reinforce the comments made by S. Konovalov (C7404–C7407, 5/11/2015). There is what*

I consider to be a significant flaw with the paper in that they base the bulk of their conclusions on a severely under sampled time-period.
A: In answer to this general comment (also raised by the first reviewer), we considered additional Argo floats extending the study period to the end of 2015.

C: *The interpolation that the authors perform for the majority of the basin between 1999-2013 (and to a lesser extent, 1986-1998) is difficult to trust due to the paucity of data coverage. Even the best interpolation scheme in the world is only as good as the input data.*
A: No spatial interpolations are done for restricted periods. The spatial climatologies presented in Fig. 3 are constructed considering the entire WOD dataset.

C: *I'm also left wondering how sensitive the analysis is to changes in selected oxygen threshold of* 20 μM. *The latter will greatly impact oxygen penetration depth estimates as the oxycline not only experiences vertical migration but also strong changes in gradient over the past 50 years.*
A: In this precise case, we could not decide whether the remark on strong gradient change was specific to the Baltic Sea. Nevertheless, considering oxygen inventory (the vertical integral) as a diagnostic was specifically intended to answer this question, as this diagnostics is particularly robust against the choice of a particular threshold. A rough computation gives 200 mmol/m3 *100 m = 20.000 mol/m2 for the upper part (above 20μM) against 10 mmol/m3 *30 m = 300 mmol/m2 for the lower part. Extending the vertical integration beyond the threshold would change the oxygen content by a few percent at best.

C: *The paper presents interesting results and a novel approach to estimating the variability of the Baltic oxygen content, but the authors need to do more to convince the reader that their study is robust due to the severe lack of data between 1993-2003. Is their method still functional in this context? Much more information needs to be provided on the results of the DIVA analysis for the reader to not dismiss the work as suffering from the issues described above.*
A: We extended the description of the DIVA algorithm to avoid any confusion on the analysis procedure.

C: *I personally have no issue with the inclusion of Argo data, although the authors should make a statement reminding the reader of the possible accuracy/precision issues inherent to Argo float oxygen measurements..*
A: This is now more precisely commented in the data description section

.

C: *.. but agree that a more in-depth study of patchiness is necessary. I suspect there is sufficient data available from the winklers to build empirical variograms and identify scales of variability.*
A: The correlation length used in the DIVA analysis was evaluated in Capet et al. (2014). We would prefer to avoid enlarging further the manuscript. Please refer to answer to S. Konovalov regarding the patchiness of Figure 3c.

C: *The authors present some good figures, but need more attention to detail in the axis, labels and captions. Many captions would benefit from being fleshed out. I would also consider adding an additional figures; a diagram indicating the relative depth of the surface, bottom and CIL water masses, with a mean oxygen, H2S and either T&S or density profiles overlaid. I leave this to the author's discretion whether they feel it is necessary or not, but I believe it would complement the introduction well for readers less acquainted with the Baltic region.*
A: We could add a figure with average temperature, density and oxygen profiles, and detailing the diagnostics

. **C:** *Although the abstract sounds a bit stilted (I would suggest reworking it very slightly for better legibility), the rest of the manuscript reads wells. The introduction is excellent, and covers the topic well. The methods section relating to the DIVA analysis must be expanded to reassure the reader that the method can cope with the huge variability of data density. The results section is brief, but to the point and highlights the important aspects, but again I would add a section providing technical results from the DIVA analysis (assessment of variability, variability of trends identified).*
A: As the trend identified for a given year is the mean of the misfits of this year data with respect to the overall climatology (Eq. A3 in the appendix), we could compute for every year the standard error of this mean (sample standard deviation/sqrt(N))

. **C:** *The discussion feels rushed; this does not impact the quality of the conclusion, rather it is my opinion that the reader would benefit from being guided through the logic and argument a bit more, particularly when relating conclusions in text to Figure 5. Finally, the conclusions were surprisingly disconnected from the rest of the paper: the last paragraph seems to bear little relation to the actual results or conclusions.*
A: The discussion will be detailed. We removed the last paragraph.

2.2 Minor Comments

C: */8: originated -¿ originating*
A: Corrected

C: *16238/8: went drifting -¿ drifted*
A: Corrected

C: *16239 and onwards: climatology cannot be detrended. Please correct the language throughout and provide a better explanation of what you mean.*
A: Ok for avoiding the terms "detrended climatology". Please refer to the new appendix for the description of the method.

C: *16240/13: the spatial variability needs further explaining; I feel at the moment there is insufficient information to fully understand what the authors are saying.*
A: Decription will be improved.

C: *16242/1-5: I'm struggling to follow the logic, please detail further.*
A: Decription will be improved.

C: *16242/6-8: What is the importance of solubility in this analysis? Does the same trend show in % saturation?*
A: This is a very pertinent remark. However we did not consider oxygen in terms of saturation but in absolute value. We would prefer to defer this analysis to a further extended work identifying more precisely the mechanisms underlying the deoxygenation trend depicted here.

C: *16244/1: arose -¿ arise*
A: Corrected

2.3 FIGURES

C: *Figure 1 caption could do with more details, mainly repeating the source and criteria for the profiles being kept so that it can stand independently.*
A: The Caption will be extended accordingly.

C: *Figure 2: Please expand axis labels to full words.*
A: lon and lat have been considered obvious and removed.

C: *Figure 3 caption also needs rephrasing. For example, what trends were removed (instead of saying simply detrended). The oxygen threshold needs to be stated. Also, if I understand correctly "oxygen penetration density anomaly" is incorrect; it's not an anomaly but rather the "oxygen density penetration" or "mean density at the upper oxic boundary"? Units should be written correction (kg m-3, rather than kg/m3). Also... how can climatology be detrended?*
A: Done

C: *Figure 4: units need to be described correctly for each linear trend: decades-1 needs to be added for each. This isn't a nature paper, you have the space now. Units should be written correction (kg m-3, rather than kg/m3).*
A: Done

C: *Figure 5: Units should be written correction (mol m-2, rather than mol/m2). I would say "Frequency distribution" rather than "Distribution density" to avoid confusion with physical density and, in my opinion, the term is more accurate.*
A: Done

A The DIVA detrending algorihtm

DIVA (Data-Interpolating Variational Analysis) is a method for spatial interpolation. Its principle is to construct an analyzed field φ that satisfies a set of constraints expressed in the form of a cost function over a spatial domain Ω. The cost function is made up of (1) an *observation constraint*, which penalizes the misfit between data and analysis, and (2) a *smoothness constraint*, which penalizes the irregularity of the analyzed field (gradients, laplacian etc).

Let us assume that we work with data anomalies, i.e. a reference (or background) field is subtracted from the data points prior the analysis. For N data anomalies d_i at locations (x_i, y_i), the cost function reads, in Cartesian coordinates:

$$\begin{aligned} J[\varphi] &= \int_\Omega \left(\boldsymbol{\nabla\nabla}\varphi : \boldsymbol{\nabla\nabla}\varphi + \alpha_1 \boldsymbol{\nabla}\varphi \cdot \boldsymbol{\nabla}\varphi + \alpha_0 \varphi^2 \right) \mathrm{d}\Omega \\ &+ \sum_{i=1}^{N} \mu_i \left[d_i - \varphi(x_i, y_i) \right]^2 = J_{\mathrm{smooth}}[\varphi] + J_{\mathrm{obs}}[\varphi], \end{aligned} \tag{1}$$

where μ_i, α_0 and α_1 are coefficients related to characteristics of the dataset. $\boldsymbol{\nabla}$ is the horizontal gradient operator and $\boldsymbol{\nabla\nabla}\varphi : \boldsymbol{\nabla\nabla}\varphi = \sum_i \sum_j (\partial^2\varphi/\partial x_i \partial x_j)\,(\partial^2\varphi/\partial x_i \partial x_j)$, the generalization of the scalar product of two vectors.

The first term of (1) measures the spatial variability (curvature, gradient and value) of the analyzed field and is identified as the smoothness constraint. The second term is a weighted sum of data-analysis misfits and is identified as the observation constraint: it tends to pull the analyzed field towards the observations. The coefficients of (1) can be determined from: (1) the relative weights w_i attributed to each observation d_i, (2) the correlation length L and (3) the signal-to-noise ratio λ (Troupin et al., 2012). The analyses presented in this study were achieved with equal weights $w_i = 1$.

The minimization of 1 is solved over Ω with a finite-element technique (Brasseur et al., 1996) which excludes data influence across land points Troupin et al. (2010).

The detrending algorithm, presented in (Capet et al., 2014) with synthetic and real case studies, proceeds as follows.

Input data can be classified amongst the different classes C_j (e.g. 1990, 1991, ...) of a given group C (e.g. the year). The observation constraint of the functional (1) can then be rewritten by including an unknown trend value for each class $(d_{C_1}, d_{C_2}, \ldots)$:

$$\begin{aligned} J_{\mathrm{obs}}[\varphi] &= \sum_{i \in C_1} \mu_i \left[d_i - d_{C_1} - \varphi(x_i, y_i) \right]^2 \\ &+ \sum_{i \in C_2} \mu_i \left[d_i - d_{C_2} - \varphi(x_i, y_i) \right]^2 + \ldots \end{aligned} \tag{2}$$

If the function $\varphi(x, y)$ were known, minimization with respect to each of the unknowns d_{C_j} would yield

$$d_{C_1} = \frac{\sum_{i \in C_1} \mu_i \left[d_i - \varphi(x_i, y_i) \right]}{\sum_{i \in C_1} \mu_i} \tag{3}$$

and similarly for the other classes: the trend for each class is the weighted misfit of the class with respect to the overall analysis.

Using an analysis without detrending as a first guess for φ, trends are computed for each classes in each group and subtracted from the original data. Following this, a new analysis is performed, the trends are recalculated, and the iterations continue until a specified convergence criterion is fulfilled. The procedure can be generalized with several groups of classes (e.g. year, month, time of the day, ...). The present study considered years and months.

The DIVA software and up-to-date related informations can be found on
http://modb.oce.ulg.ac.be/mediawiki/index.php/DIVA.

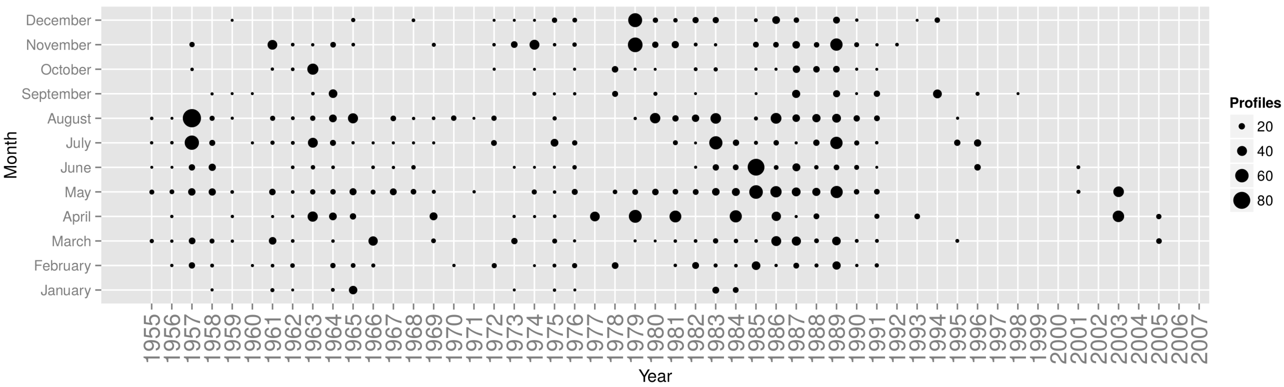

Figure 1: Temporal distribution of the ship-based oxygen profiles merged from the World Ocean Database, R/V Knorr 2003 and R/V Endeavor 2005 campaigns. Only the profiles containing at least 5 observation depths, one observation above 30 m depth and one record with $[O_2] < 20$ μM were considered.

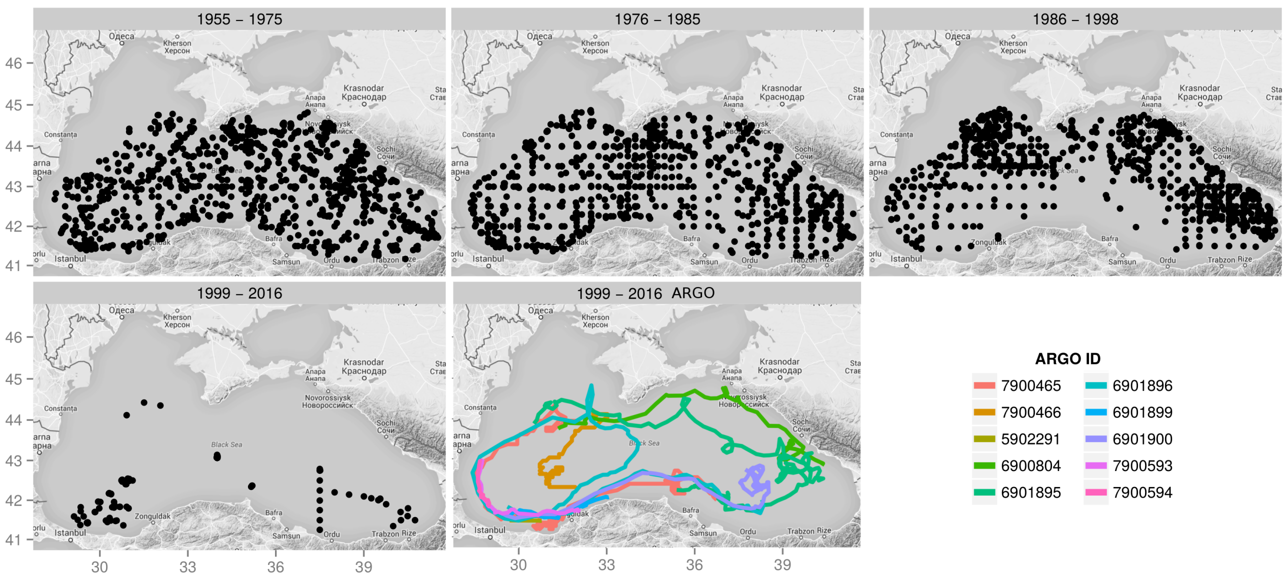

Figure 2: Distribution of the ship-based oxygen profiles (Fig. 1) available for each period (black dots). The last panel displays the trajectories of the ARGO floats. Number of profiles for each period are given in the text. Map data: ©Google 2015.

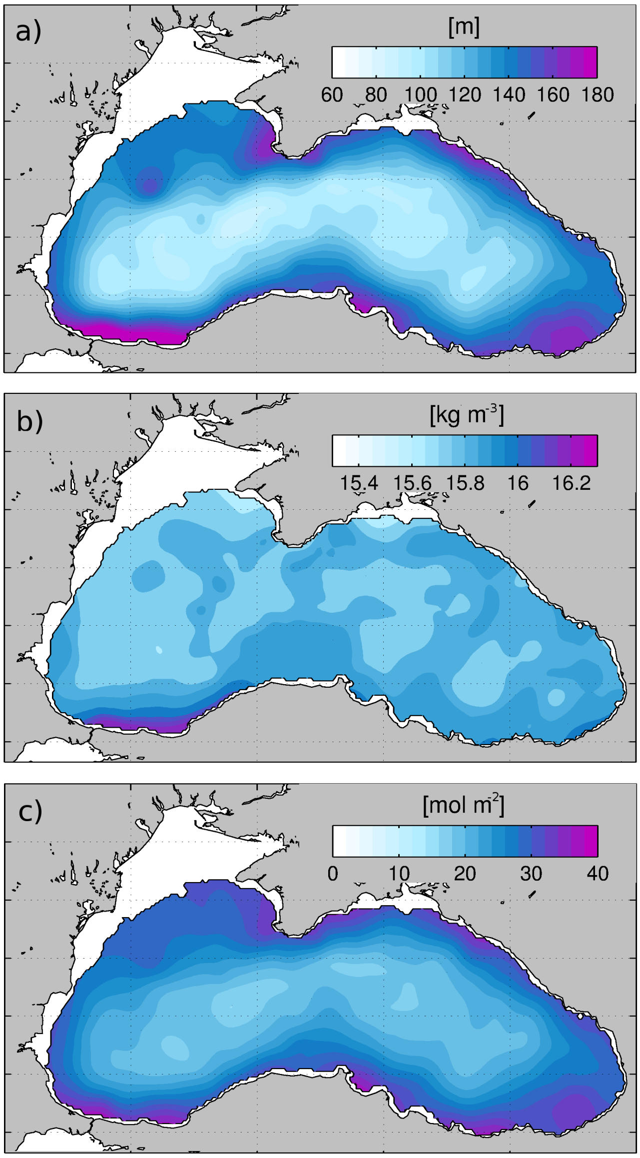

Figure 3: Annual climatologies of **(a)** oxygen penetration depth (where $[O_2] = 20\ \mu$M), **(b)** potential density anomaly at oxygen penetration depth and **(c)** oxygen inventory . These spatial climatologies were constructed from the WOD dataset (1955–2005), accounting for temporal variability and uneven data distribution (see Sect. 2.3).

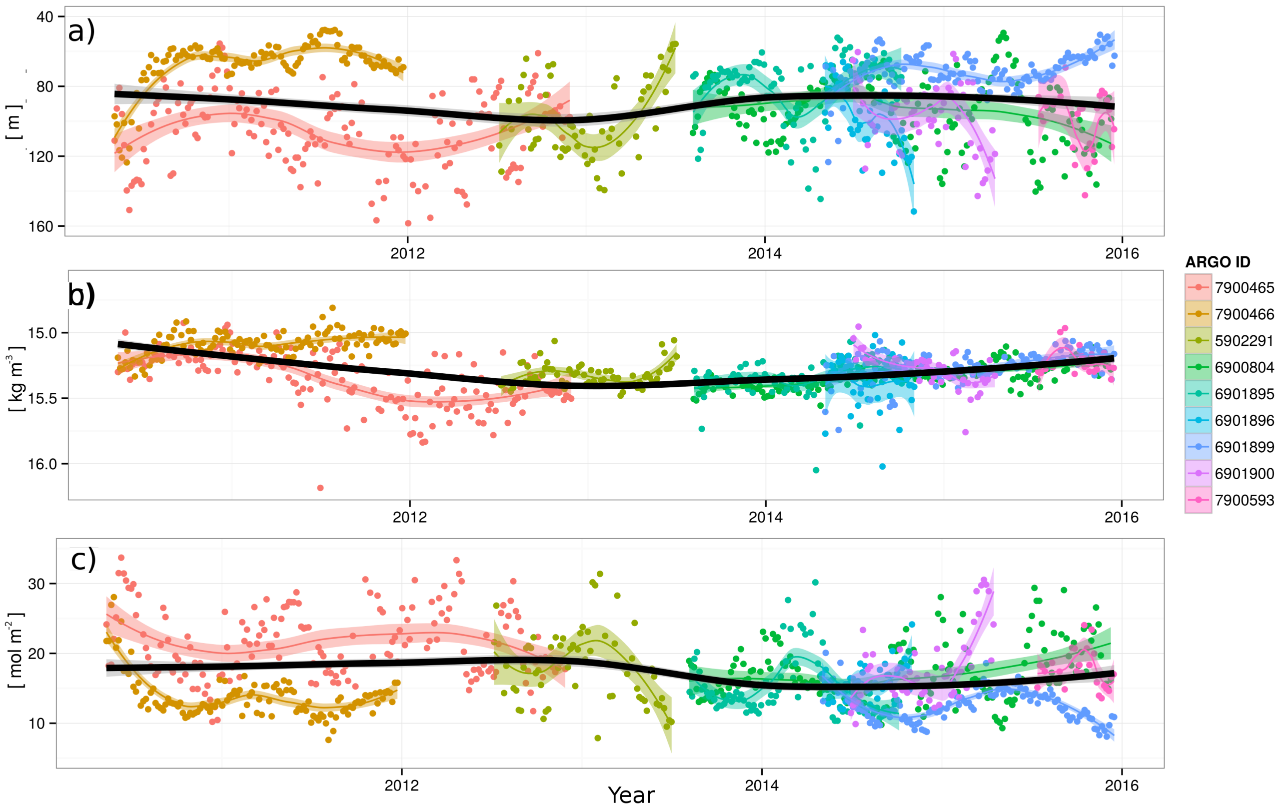

Figure 4: Diagnostics of (a) Oxygen penetration depth, (b) Oxygen penetretion density levels and (c) oxygen invetory derived from ARGO floats. The color legends gives the unique ARGO identification number of the floats. Coloured lines and filled area indicate smoothed time series for each float (second degree loess smoother, span=0.75, 0.95 confidence intervals). The black line and grey shaded area are the smoothed time series obtained when considering all floats (reported on Fig. 5)
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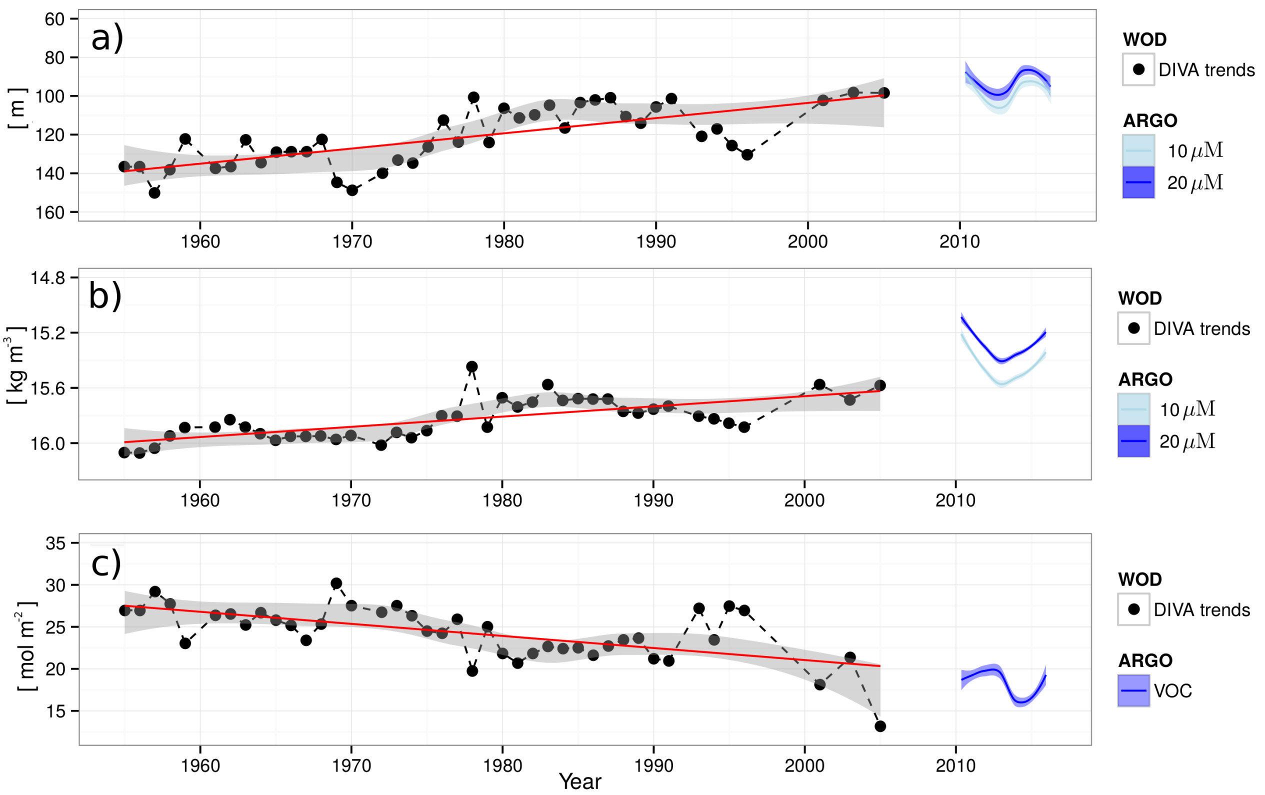

Figure 5: Trends of (a) oxygen penetration depth, (b) oxygen penetration density level (σ_T) and (c) oxygen inventory deduced from (dots) DIVA analysis of ship-based casts and (blue) ARGO floats. On (a) and (b), the diagnostics from ARGO are also shown for the lower thresold of 10 μM to acknowledge potential difference between Winkler and ARGO data. Red lines: the linear trends assessed from the WOD data set are -7.9 m decades^{-1}, -0.11 kg m^{-3} decades^{-1} and -1.44 mol O m^{-2} decades^{-1} per decades for (a), (b) and (c), respectively.

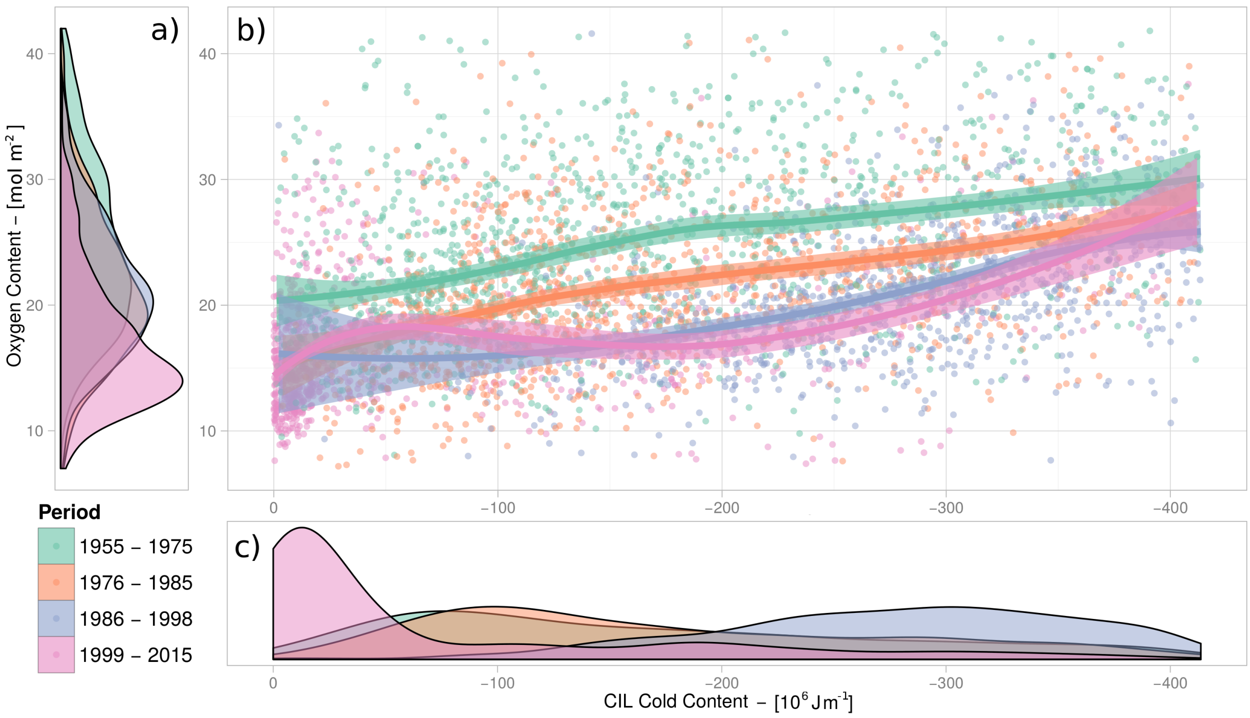

Figure 6: Impact of convective ventilation on oxygen inventory. Frequency distributions of (a) oxygen inventory and (c) Cold Intermediate Layer (CIL) cold content diagnosed from ship-based and ARGO floats for different periods (color legend). **(b)** Loess regressions (second degree polynomials, span=0.75, Cleveland et al. (1992)) between oxygen inventory and CIL cold content for the different periods (confidence interval $\alpha = 0.99$). The positive relationships observed during each period illustrate the ventilating action of CIL formation as a source of oxygen to the intermediate levels. The shift of these relationships towards lower oxygen inventories indicates shift in the oxygen budgets (higher consumption) that are independent of the intensity of CIL formation.

References

Bittig, H. C. and Körtzinger, A.: Tackling oxygen optode drift: Near-surface and in-air oxygen optode measurements on a float provide an accurate in-situ reference, Journal of Atmospheric and Oceanic Technology, p. 150310071431006, 2015.

Brasseur, P., Beckers, J.-M., Brankart, J.-M., and Schoenauen, R.: Seasonal temperature and salinity fields in the Mediterranean Sea: Climatological analyses of a historical data set, Deep-Sea Research Part I : Oceanographic Research Papers, 43, 159–192, doi:10.1016/0967-0637(96)00012-X, 1996.

Capet, A., Troupin, C., Carstensen, J., Grégoire, M., and Beckers, J.-M.: Untangling spatial and temporal trends in the variability of the Black Sea Cold Intermediate Layer and mixed Layer Depth using the DIVA detrending procedure, Ocean Dynamics, 64, 315–324, 2014.

Cleveland, W. S., Grosse, E., and Shyu, W. M.: Local regression models, in: Statistical models in S, edited by Chambers, J. and Hastie, T., Wadsworth & Brooks/Cole, 1992.

Johnson, K. S., Plant, J. N., Riser, S. C., and Gilbert, D.: Air Oxygen Calibration of Oxygen Optodes on a Profiling Float Array, Journal of Atmospheric and Oceanic Technology, 32, 2160–2172, 2015.

Stanev, E., He, Y., Grayek, S., and Boetius, A.: Oxygen dynamics in the Black Sea as seen by Argo profiling floats, Geophysical Research Letters, 2013.

Takeshita, Y., Martz, T. R., Johnson, K. S., Plant, J. N., Gilbert, D., Riser, S. C., Neill, C., and Tilbrook, B.: A climatology-based quality control procedure for profiling float oxygen data, Journal of Geophysical Research: Oceans, 118, 5640–5650, 2013.

Troupin, C., Machín, F., Ouberdous, M., Sirjacobs, D., Barth, A., and Beckers, J.-M.: High-resolution climatology of the North-East Atlantic using Data-Interpolating Variational Analysis (DIVA), Journal of Geophysical Research, 115, C08 005, doi:10.1029/2009JC005512, URL `http://www.agu.org/pubs/crossref/2010/2009JC005512.shtml`, 2010.

Troupin, C., Sirjacobs, D., Rixen, M., Brasseur, P., Brankart, J.-M., Barth, A., Alvera-Azcárate, A., Capet, A., Ouberdous, M., Lenartz, F., Toussaint, M.-E., and Beckers, J.-M.: Generation of analysis and consistent error fields using the Data Interpolating Variational Analysis (DIVA), Ocean Modelling, 52-53, 90–101, doi:10.1016/j.ocemod.2012.05.002, URL `http://www.sciencedirect.com/science/article/pii/S1463500312000790`, 2012.